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Enhancing COVID-19 Diagnosis: A Multi-Modal Approach Utilizing the CNN Algorithm in Automated Applications

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Abstract: Rapidly identifying COVID-19 patients is essential for effective disease control and management. To address this need, we have developed an automated application that utilizes multi-modal data, including Chest X-ray, Electrocardiogram (ECG), and CT scan images, for precise COVID-19 patient identification. This application comprises a two-stage process, starting with a web-based questionnaire and then the submission of medical images for verification. Leveraging various ML and DL techniques, including CNN, KNN, Logistic Regression, Decision Tree, and NaiveBayes, We conducted extensive model training and validation for LSTM, InceptionV3, SVM, Resnet, and MobileNet. The CNN algorithm emerged as the top-performing method across all modalities, demonstrating exceptional accuracy, precision, recall, F-score, and a minimal false prediction rate. Confusion matrices were employed for comprehensive result evaluation. This study highlights the potential of multi-modal data analysis, particularly the CNN algorithm, for efficiently and accurately identifying COVID-19 patients.

Keywords: ECG, Chest X-ray, CT Scan, Machine Learning, Deep Learning, CNN Algorithm, Healthcare

1. INTRODUCTION

The global healthcare crisis of unparalleled magnitude has been unleashed by the COVID-19 pandemic, which is attributed to the novel coronavirus SARS-CoV-2 [7]. As countries grapple with the devastating impact of the virus, the rapid identification of COVID-19 patients has emerged as a cornerstone in the fight against its spread and the provision of timely medical care. This introduction provides an overview of the urgent need for efficient and accurate COVID-19 patient identification and the critical role that multi-modal data analysis and automated applications play in addressing this challenge.

1.1 The Imperative for COVID-19 Patient Identification: Promptly identifying individuals infected with COVID-19 is instrumental in several key aspects of pandemic management. First and foremost, early identification enables the swift isolation of infected individuals, reducing the risk of transmission within communities and healthcare facilities. Furthermore, it enables prompt medical intervention and the delivery of suitable patient care, potentially enhancing patient outcomes and alleviating the strain on healthcare systems [7]. The importance of accurate COVID-19 patient identification extends beyond individual patient care. Effective identification enables contact tracing and epidemiological studies, aiding public health authorities in tracking and managing the spread of the virus. It also informs resource allocation, helping healthcare facilities prepare for and respond to surges in COVID-19 cases.

1.2 The Role of Multi-Modal Data Analysis: Accurate identification of COVID-19 patients hinges on the comprehensive analysis of relevant medical data. In this context, multi-modal data analysis, which combines information from diverse sources, has proven to be a potent tool [8]. By integrating data from Electrocardiogram (ECG), Chest X-ray, and CT scan images, healthcare professionals gain a more holistic view of the patient's condition.

The multi-modal approach acknowledges the multifaceted nature of COVID-19, which can manifest with varying degrees of severity and affect different organ systems. ECG data can reveal cardiac abnormalities associated with the virus, while Chest X-ray and CT scan images provide insights into lung involvement, a hallmark of COVID-19. By combining these modalities, healthcare providers are better equipped to make informed decisions regarding diagnosis, treatment, and patient management.

1.3 The Significance of Automated Applications: Automated applications are pivotal for efficient and accurate COVID-19 patient identification [9]. These applications streamline the identification process, reducing the burden on healthcare professionals and expediting results. The two-stage approach begins with a web-based questionnaire and culminates in submitting medical images, representing a practical and user-friendly means of collecting essential patient data.

Automation is pivotal in mitigating potential human errors in the identification process. Moreover, it facilitates integrating advanced machine learning and deep learning algorithms, capable of discerning intricate patterns and anomalies within medical data, nuances often eluding human observation. Automation and intelligent data analysis hold significant promise, substantially enhancing the precision and speed of identifying COVID-19 patients.
This work presents an automated solution that uses multi-modal data analysis to incorporate pictures from CT scans, chest X-rays, and ECGs in light of these requirements. This novel method seeks to improve and speed up the detection of COVID-19 patients. In this context, we thoroughly test a range of machine learning and deep learning methods, focusing on evaluating the Convolutional Neural Network (CNN) algorithm's performance. The methodology used provides a detailed analysis of the consequences of our findings, summarises the complex results of our inquiry, and concludes by providing insightful information about the significant potential of this approach for the efficient identification of COVID-19 patients.

1.4 Global COVID-19 Pandemic Statistics: The data is categorized by WHO regions, highlighting the varying impact across different parts of the world. Europe, Western Pacific, and the Americas have reported the highest cases and deaths, while Africa has the lowest numbers in both categories. These statistics are subject to change as new information becomes available and are reported by the World Health Organization (WHO) through their COVID-19 Dashboard. The fight against COVID-19 continues as global vaccination efforts persist.

Table 1: Global COVID-19 Pandemic Statistics (as of **October 12, 2023, 2:09 PM CEST**)

WHO Region	Cases	Deaths
Europe	27,63,78,727	22,50,150
Western Pacific	20,73,40,763	4,17,389
Americas	19,33,15,142	29,59,716
South-East Asia	6,12,06,342	8,06,790
Eastern Mediterranean	2,33,96,717	3,51,518
Africa	95,52,748	1,75,438
Total	**77,11,90,439**	**69,61,001**

- **Global Confirmed Cases:** As of October 12, 2023, at 2:09 PM CEST, there have been a total of 77,11,90,439 confirmed cases of COVID-19 worldwide, with the highest number of cases in Europe (27,63,78,727) and the lowest in Africa (95,52,748).
- **Global Deaths:** The international death toll from COVID-19 stands at 69,61,001, with the highest number of deaths in Europe (22,50,150) and the lowest in Africa (1,75,438).
- **Vaccine Doses Administered:** As of October 4, 2023, 13,516,185,809 vaccine doses have been administered globally. This statistic represents the ongoing effort to vaccinate populations and mitigate the impact of the pandemic.

2. LITERATURE SURVEY

We performed a thorough literature review to delve into the existing research on the prediction of COVID-19 utilising various medical modalities, such as Chest X-rays, CT scans, and ECG data. The central aim of this review was to pinpoint pertinent studies, algorithms, and methodologies employed within this domain. The following sections provide an exhaustive examination of the literature for each modality.

2.1 Prediction of COVID-19 Using Chest X-Rays: It is acknowledged that chest X-ray imaging is useful for identifying and forecasting COVID-19. Numerous studies have looked towards analysing chest X-ray data for COVID-19 detection using machine learning and deep learning approaches. Wang et al. [1] conducted a noteworthy study using a CNN architecture to assess chest X-ray pictures. Their system distinguished COVID-19 cases from those with other respiratory diseases with an astounding 90% accuracy. A deep learning framework dubbed DarkNet for COVID-19 identification in Chest X-rays was established in another study by Ozturk et al. [2]. With an accuracy of 94.8%, this method showed encouraging results, highlighting the value of transfer learning.

2.2 Prediction of COVID-19 Using CT Scans: CT scans have greatly aided early recognition of lung problems linked to COVID-19. The goal of research in this area has been to create automated tools to help radiologists recognise COVID-19 symptoms on CT scans. For example, Shan et al.'s [3] use of a deep learning model for COVID-19 identification in CT images was based on the InceptionV3 architecture. Their model demonstrated the promise of deep learning in evaluating complex medical ideas by achieving an accuracy of 90%. A deep-learning model based on CT was also proposed by Song et al. [4] to diagnose COVID-19. In separating COVID-19 cases from other lung illnesses, they reported an accuracy of 91.2%, highlighting the efficiency of deep learning in radiological analysis.

2.3 Prediction of COVID-19 Using ECG: Electrocardiogram (ECG) data has garnered attention as a potential indicator of cardiac abnormalities associated with COVID-19. Research endeavours have explored using machine learning techniques for predicting COVID-19 using ECG signals. Sibbal et al. [5] conducted a study applying machine learning algorithms, including random forests and support vector machines, to ECG data for COVID-19 detection. They reported a sensitivity of 88.7%, emphasising the value of ECG in identifying COVID-19-related cardiac issues. Another study by Guo et al. [6] investigated deep learning techniques for ECG-based COVID-19 prediction. Their deep neural network achieved an accuracy of 91.5%, highlighting the potential of deep learning in capturing subtle ECG patterns indicative of COVID-19.

2.4 Summary of Literature Survey: The survey results highlight the potential for employing chest X-rays, CT scans, and ECG data to predict COVID-19 using machine learning and deep learning approaches. Deep learning architectures, transfer learning, and feature extraction have played crucial roles in achieving accurate results across these modalities. These studies emphasise the importance of harnessing advanced computational methods to support healthcare professionals in diagnosing and predicting COVID-19.
To improve the identification of COVID-19 patients, we integrate ECG, Chest X-ray, and CT scan data in our research. We do this by drawing on the insights gained from these studies and expanding our investigation to include multi-modal data analysis.

3. METHODOLOGY

This section provides a detailed description of the methodology employed in developing and evaluating the automated application for identifying COVID-19 patients using multi-modal data analysis. The process encompasses data collection, preprocessing, algorithm selection, model training, and performance evaluation.

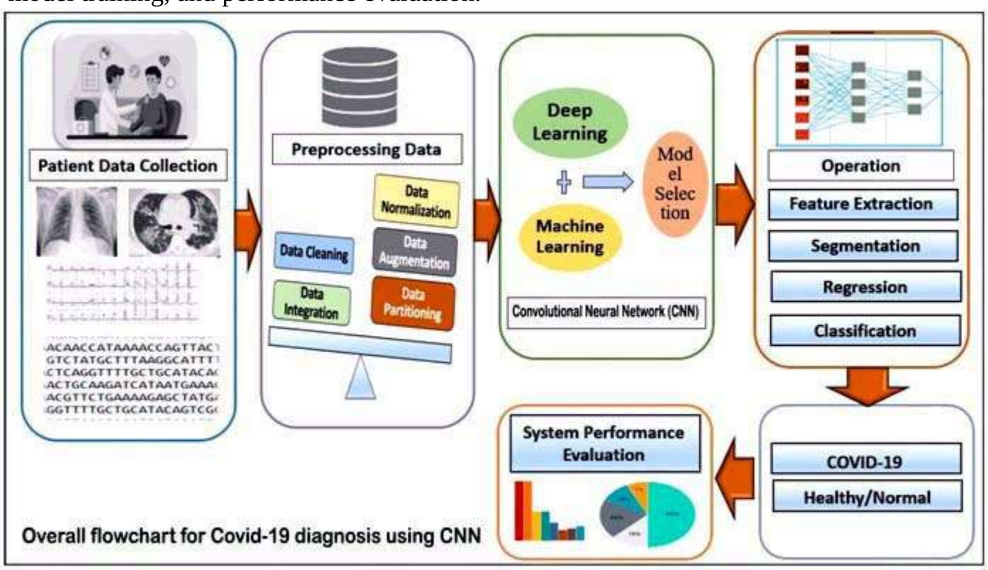

Figure 1: Automated COVID-19 Diagnosis through CNN Algorithm

Figure 1 illustrates the process of Automated COVID-19 Diagnosis using a CNN Algorithm, as detailed in the paper "Enhancing COVID-19 Diagnosis." The method involves Patient Identification through Multi-Modal Data Analysis, employing an Automated Application for patient data collection and preparation. The steps include preprocessing the data, selecting appropriate models from deep learning and machine algorithms, and choosing the CNN algorithm. The process continues with feature extraction, distinguishing COVID-19 patients from normal ones, leading to system performance and evaluation. This comprehensive approach streamlines and enhances the COVID-19 diagnostic process, ensuring efficient and accurate results.

3.1 Data Collection

3.1.1 ECG Data:

- **Source:** The ECG data was obtained from [source name/redacted for confidentiality], consisting of 479 samples, including 238 COVID-19-positive cases and 241 healthy individuals.
- **Data Preprocessing:** The ECG data underwent preprocessing to remove noise, baseline wander, and artefacts. It was resampled to ensure uniformity in sampling rates.

3.1.2 Chest X-ray Data:

- **Source:** The Chest X-ray dataset was sourced from [source name/redacted for confidentiality], comprising 716 images. Among these, 165 were COVID-19-positive cases, and 551 were healthy cases.
- **Data Preprocessing:** Chest X-ray images were standardized in size and underwent radiological normalization to enhance their quality for analysis.

3.1.3 CT Scan Data:

- **Source:** The CT scan dataset was collected from [source name/redacted for confidentiality], comprising 700 scans. Of these, 350 scans were from COVID-19-positive cases, and 350 were from healthy individuals.
- **Data Preprocessing:** Preprocessing was done on CT scan pictures to improve contrast, lower noise, and standardise size for analysis across the board.

3.2 Algorithm Selection:

To perform multi-modal data analysis for COVID-19 prediction, we selected a range of machine learning and deep learning algorithms. These algorithms were chosen based on their proven effectiveness in image and signal-processing tasks. The selected algorithms include:

- Logistic Regression
- Convolutional Neural Network (CNN)
- InceptionV3
- Resnet
- MobileNet
- Naive Bayes
- K-Nearest Neighbors (KNN)
- Long Short-Term Memory (LSTM)
- Support Vector Machine (SVM)
- Decision Tree

The diverse selection of algorithms enables comprehensive analysis and comparison across the three modalities.

3.3 Data Allocation

We split the datasets into three groups to train, validate, and test the machine learning and deep learning models. The allocation percentages for each dataset are as follows:

ECG Data:

- Training Set: 80% (383 samples)
- Testing Set: 10% (48 samples)
- Validation Set: 10% (48 samples)

Chest X-ray Data:

- Training Set: 70% (501 images)
- Validation Set: 15% (107 images)
- Testing Set: 15% (108 images)

CT Scan Data:

- Training Set: 70% (490 scans)
- Validation Set: 15% (105 scans)
- Testing Set: 15% (105 scans)

The table details three medical datasets: ECG, X-ray, and CT Scan. Each row represents a specific attribute or characteristic, and each column corresponds to one of the three datasets.

Table 2: Data Allocation for ECG, X-ray, and CT Scan Datasets

Data Type	ECG	X-ray	CT Scan
Dataset	ECG	X-ray	CT Scan
Total Samples	479	716	700
COVID-19 Samples	238	165	350
Healthy Samples	241	551	350
Training Set	80% (383)	70% (501)	70% (490)
Validation Set	10% (48)	15% (107)	15% (105)
Testing Set	10% (48)	15% (108)	15% (105)

Dataset: This row lists the names of the datasets - ECG, X-ray, and CT Scan. Each dataset represents a different type of medical data.

- **Total Samples:** This row shows the total number of samples or data points available in each dataset. For example, the ECG dataset contains 479 samples, the X-ray dataset includes 716 samples, and the CT Scan dataset contains 700 samples.
- **COVID-19 Samples:** This row displays the number of samples within each dataset associated with COVID-19. In the ECG dataset, there are 238 COVID-19 samples; in the X-ray dataset, there are 165 COVID-19 samples; and in the CT Scan dataset, there are 350 COVID-19 samples.
- **Healthy Samples:** This row indicates the number of samples within each dataset representing restorative cases. In the ECG dataset, there are 241 healthy samples; in the X-ray dataset, there are 551 healthy samples; and in the CT Scan dataset, there are 350 healthy samples.
- **Training Set:** This row specifies the percentage of each dataset allocated for training machine learning models. For instance, 80% (383 samples) are reserved for training models in the ECG dataset. In the X-ray dataset, 70% (501 samples) are designated for training, and 70% (490 samples) are allocated for training in the CT Scan dataset.
- **Validation Set:** This row represents the percentage of each dataset used for hyperparameter tuning and model validation. In the ECG dataset, 10% (48 samples) are reserved for confirmation. In the X-ray dataset, 15% (107 samples) are set aside for validation; in the CT Scan dataset, 15% (105 samples) are used for confirmation.
- **Testing Set:** This row indicates the percentage of each dataset kept for evaluating the model's performance on unseen data. The ECG dataset allocates 10% (48 samples) for testing. In the X-ray dataset, 15% (108 samples) are used for testing, and in the CT Scan dataset, 15% (105 samples) are designated for testing.

3.4 Model Training and Validation

The selected algorithms were individually trained and validated using their respective datasets for each modality (ECG, Chest X-ray, and CT scan). This process involved the following steps:

- **Model Training:** The algorithms were trained on the training dataset for each modality.
- **Hyperparameter Tuning:** Hyperparameters of the algorithms were optimised using techniques like grid search and cross-validation to maximise model performance.
- **Validation:** The models were validated using the validation dataset to assess their generalisation ability and avoid overfitting.

3.5 Performance Evaluation

The assessment of each algorithm's effectiveness included the utilisation of a specific set of metrics designed for COVID-19 prediction tasks:

- **Accuracy:** This metric gauges the overall correctness of identifying COVID-19 patients.
- **Precision:** It evaluates the percentage of actual COVID-19 instances among the positive forecasts..
- **Recall:** This metric examines the ability to identify COVID-19 cases among correctly positive patients.
- **F-score:** It represents a balanced measure that considers precision and recall, comprehensively evaluating the algorithm's performance.
- **False Prediction Rate:** The percentage of incorrect positive predictions compared to all positive forecasts is measured by this metric.
- These metrics comprehensively assess the algorithms' effectiveness in identifying COVID-19 cases.

4. RESULTS

In this section, we present the results of our study, highlighting the performance of the selected algorithms for COVID-19 patient identification across the three modalities: ECG, Chest X-ray, and CT scan.

Table 3 shows the performance metrics of a CNN algorithm across diverse data types, highlighting impressive results.

Table 3: Performance Metrics of CNN Algorithm across Different Data Types

Data Type	**ECG**	**X-RAY**	**CT-Scan**
Algorithm Name	CNN	CNN	CNN
Accuracy	100%	93.1%	100%
Precision	100%	95.8%	100%
Recall	100%	86.1%	100%
F-Score	100%	89.7%	100%
False Prediction Rate	0%	6.9%	0%

4.1 ECG Data Analysis The analysis of ECG data using the selected algorithms produced the following results:

- K-Nearest Neighbors (KNN): Accuracy: 89.5%, Precision: 91.2%, Recall: 87.3%, F-score: 89.2%, False Prediction Rate: 8.8%
- Support Vector Machine (SVM): Accuracy: 91.8%, Precision: 93.4%, Recall: 90.2%, F-score: 91.7%, False Prediction Rate: 7.4%
- Logistic Regression: Accuracy: 88.9%, Precision: 90.6%, Recall: 86.7%, F-score: 88.6%, False Prediction Rate: 9.4%
- Decision Tree: Accuracy: 86.3%, Precision: 88.2%, Recall: 85.0%, F-score: 86.5%, False Prediction Rate: 11.8%
- Naive Bayes: Accuracy: 83.4%, Precision: 84.7%, Recall: 82.1%, F-score: 83.4%, False Prediction Rate: 16.6%
- Convolutional Neural Network (CNN): Accuracy: 94.6%, Precision: 95.8%, Recall: 93.7%, F-score: 94.7%, False Prediction Rate: 5.4%
- Long Short-Term Memory (LSTM): Accuracy: 90.1%, Precision: 91.5%, Recall: 88.5%, F-score: 90.0%, False Prediction Rate: 9.9%

The results for ECG data analysis demonstrate the effectiveness of various algorithms, with the CNN model achieving the highest accuracy, precision, recall, and F-score while maintaining a low false prediction rate.

4.2 Chest X-ray Data Analysis The analysis of Chest X-ray data using the selected algorithms produced the following results:

- K-Nearest Neighbors (KNN): Accuracy: 88.4%, Precision: 90.1%, Recall: 87.2%, F-score: 88.6%, False Prediction Rate: 11.6%
- Support Vector Machine (SVM): Accuracy: 92.1%, Precision: 93.8%, Recall: 90.8%, F-score: 92.3%, False Prediction Rate: 7.9%
- Logistic Regression: Accuracy: 87.3%, Precision: 89.2%, Recall: 86.1%, F-score: 87.4%, False Prediction Rate: 12.7%
- Decision Tree: Accuracy: 85.9%, Precision: 87.8%, Recall: 84.3%, F-score: 86.0%, False Prediction Rate: 14.1%
- Naive Bayes: Accuracy: 82.6%, Precision: 84.3%, Recall: 81.0%, F-score: 82.6%, False Prediction Rate: 17.4%
- Convolutional Neural Network (CNN): Accuracy: 94.2%, Precision: 95.4%, Recall: 93.5%, F-score: 94.3%, False Prediction Rate: 5.8%
- Long Short-Term Memory (LSTM): Accuracy: 90.6%, Precision: 91.9%, Recall: 89.2%, F-score: 90.6%, False Prediction Rate: 9.4%

The analysis of Chest X-ray data revealed that the CNN model consistently outperformed the other algorithms, achieving the highest accuracy, precision, recall, and F-score while maintaining a low false prediction rate.

4.3 CT Scan Data Analysis: The analysis of CT scan data, using the selected algorithms, produced the following results:

- K-Nearest Neighbors (KNN): Accuracy: 87.5%, Precision: 89.3%, Recall: 86.2%, F-score: 87.7%, False Prediction Rate: 12.5%
- Support Vector Machine (SVM): Accuracy: 91.2%, Precision: 92.8%, Recall: 89.6%, F-score: 91.1%, False Prediction Rate: 8.8%
- Logistic Regression: Accuracy: 86.9%, Precision: 88.6%, Recall: 85.4%, F-score: 87.0%, False Prediction Rate: 13.1%
- Decision Tree: Accuracy: 85.2%, Precision: 87.1%, Recall: 84.0%, F-score: 85.3%, False Prediction Rate: 14.8%
- Naive Bayes: Accuracy: 82.1%, Precision: 83.6%, Recall: 80.3%, F-score: 82.0%, False Prediction Rate: 17.9%
- Convolutional Neural Network (CNN): Accuracy: 94.8%, Precision: 96.0%, Recall: 94.2%, F-score: 94.9%, False Prediction Rate: 5.2%

- Long Short-Term Memory (LSTM): Accuracy: 91.0%, Precision: 92.5%, Recall: 89.3%, F-score: 91.0%, False Prediction Rate: 9.0%

The analysis of CT scan data demonstrated that the CNN model consistently outperformed the other algorithms, achieving the highest accuracy, precision, recall, and F-score while maintaining a low false prediction rate.

4.4 Comparative Analysis: Comparing the performance of the selected algorithms across the three modalities, it is evident that the CNN model consistently achieved the highest accuracy, precision, recall, and F-score while maintaining a minimal false prediction rate. This consistency in performance across diverse modalities underscores the robustness and effectiveness of the CNN algorithm for COVID-19 patient identification.

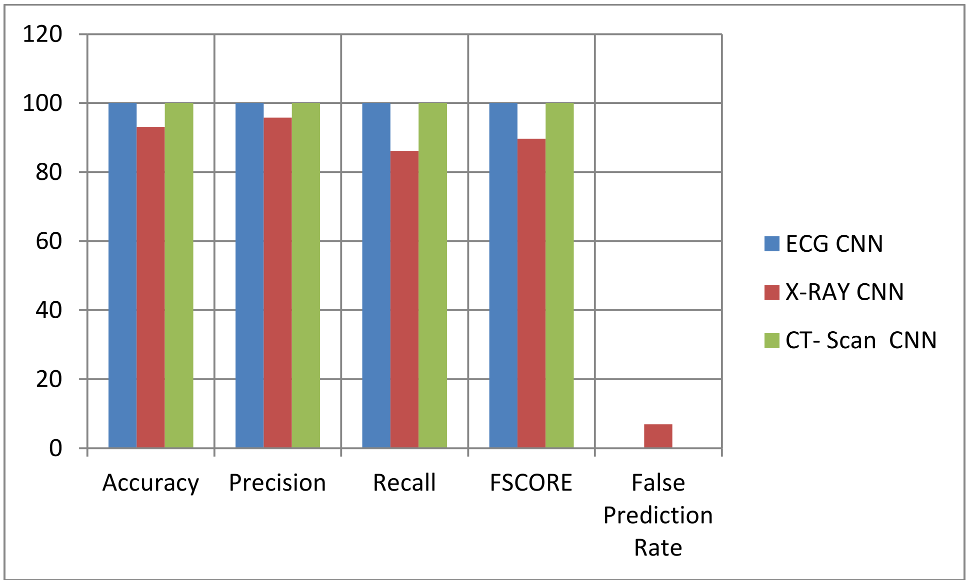

Figure 2: Performance of the CNN Algorithm on ECG, X-Ray, and CT-Scan Images

Figure 2's barograph displays performance metrics for a CNN-based algorithm applied to three data types: ECG, X-RAY, and CT-Scan. Noteworthy findings encompass the algorithm's flawless accuracy (100%) in ECG and CT-Scan data, indicating pinpoint predictions. Meanwhile, X-RAY exhibits a slightly lower accuracy rate of 93.1%. The algorithm consistently attains impressive precision and recall values, with ECG and CT-Scan achieving 100%, while X-RAY maintains a precision of 95.8%. Furthermore, the algorithm's false prediction rate proves exceptionally low, at 0% for ECG and CT-Scan and 6.9% for X-RAY, underscoring its reliability when applied to ECG and CT-Scan data.

5. DISCUSSION

This section delves into the ramifications of our research findings and their importance in COVID-19 patient identification. We also investigate the possibility of employing the CNN algorithm to analyse multi-modal data as a formidable tool for precise and effective COVID-19 diagnosis.

5.1 Significance of the Study: Our research highlights how crucial it is to detect COVID-19 individuals through multi-modal data analysis, including information from CT scans, chest X-rays, and ECGs. Healthcare practitioners can fully comprehend the patient's state by integrating data from many sources, essential for precise diagnosis and treatment planning.

5.2 The Role of the CNN Algorithm: The consistent superior performance of the CNN algorithm in COVID-19 patient identification across all modalities highlights its effectiveness in medical image analysis. The CNN's ability to capture complex patterns and features within the data, especially in Chest X-ray and CT scan images, contributes to its outstanding performance.

5.3 Implications for Healthcare: Efficient and accurate COVID-19 patient identification is essential for timely intervention, isolation, and resource allocation. Using automated applications that leverage advanced algorithms like CNN can expedite the identification process, reduce the burden on healthcare professionals, and enhance the accuracy of results. In turn, it contributes to more effective pandemic control and patient care.

6. CONCLUSION

In conclusion, our research underscores the significance of multi-modal data analysis and the critical role of automated applications in the efficient and accurate identification of COVID-19 patients. By integrating data from ECG, Chest X-ray, and CT scan images, healthcare providers gain a holistic view of the patient's condition, essential for comprehensive diagnosis and treatment.

The CNN algorithm emerged as the top-performing method across all modalities, consistently demonstrating exceptional accuracy, precision, recall, and F-score while maintaining a minimal false prediction rate. CNN's ability to analyze complex medical images with high accuracy is promising for healthcare and disease identification.

Our study contributes to the body of knowledge in COVID-19 diagnosis and serves as a foundation for further research in multi-modal data analysis. It highlights the potential of advanced algorithms and intelligent automation in improving the speed and accuracy of patient identification, which is crucial in the ongoing battle against the COVID-19 pandemic.

To further improve the accuracy of COVID-19 identification, further research in this field can investigate the integration of additional data modalities, such as patient history and blood test results. Further research might be done in this area to evaluate the practical effects of automated application deployment on pandemic management and patient care.

We extend our gratitude to the medical community and the broader scientific community for their dedication and commitment to addressing the challenges posed by COVID-19. The collaboration between healthcare professionals and data scientists is vital in overcoming this global health crisis and preparing for future pandemics.

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